

Undergraduate projects and Supervised ML

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Outline

- Introduction
- ML and Supervised ML
- Some working areas
- Implementation



Introduction

- Aims to build smart systems.
 - Trains data with predefined algorithms.
 - Make predictions or classifies for the new inputs, especially unseen inputs.
- **Machine Learning**



Introduction

- Aims to build AI models with labeled data.
 - Trains data with by minimizing the prediction errors.
 - Examples: Linear regression, decision trees, Naive Bayes, SVM, NN.
- **Supervised Machine Learning**

Supervised ML

- Load data:

```
x, y <- build_classification(sample = 1000, features = 10,  
classes = 2)
```

- Prepare training and test data.

```
x_train, x_test, y_train, y_test <- split_train_test(x,y,  
test_size=0.10)
```

- Train:

```
model <- MLAlgorithm().fit(x_train, x_test)
```

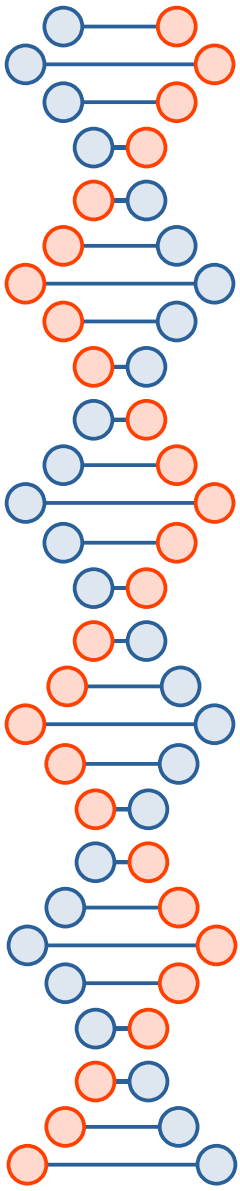
- Use:

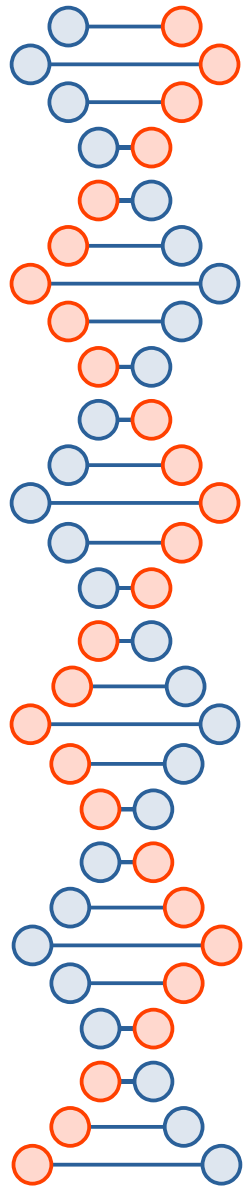
```
y_pred <- model.predict(x_test) or model.classfy(x_test)
```

- Score:

```
score <- accuracy(y_test, y_pred)
```

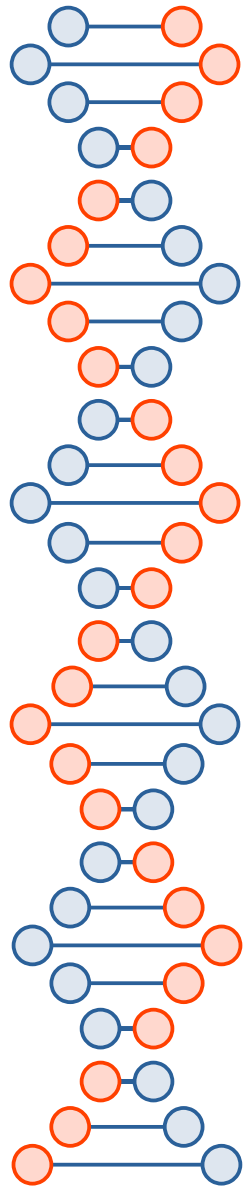
- **Steps**





Supervised ML applications

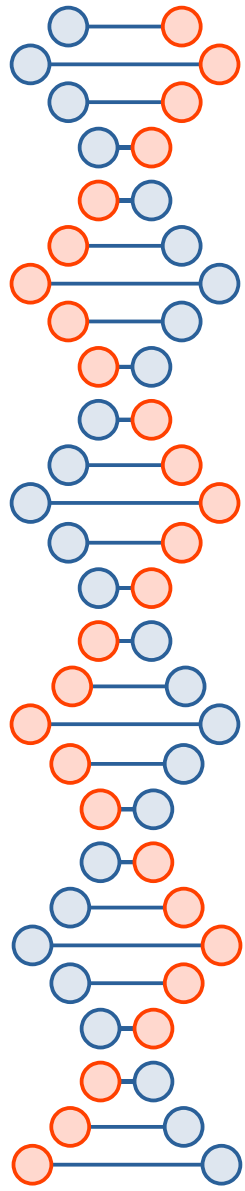
- Image and Speech recognition.
- Medical diagnosis.
- Financial, Weather forecasting.
- Natural Language Processing.
- Network Security.
- ...



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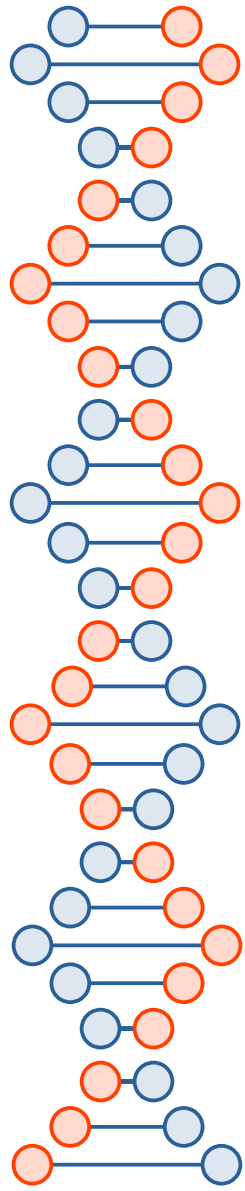
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- **Context of Spell**



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- **Scheduling and Route Planning**



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- **Graph based data modeling**



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- **Query Generation from ontology graphs**



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- **Smart contract based software development**



Hands on: Naive Bayes classifier

- Posterior Probability:

$$p(C_k|\vec{x}) = \frac{p(\vec{x}|C_k)p(C_k)}{p(\vec{x})} = \frac{p(x_1, \dots, x_n|C_k)p(C_k)}{p(x_1, \dots, x_n)}$$

where $\vec{x} = \{x_1, \dots, x_n\}$ ' $k = 1, \dots, K$.

- Using chain rule,

$$p(x_1, \dots, x_n|C_k) = p(x_1|x_2, \dots, x_n, C_k)p(x_2|x_3, \dots, x_n, C_k) \dots p(x_{n-1}|x_n, C_k)p(x_n|C_k)$$

- Naive Assumption:

$$p(x_i|x_{i+1}, \dots, x_n|C_k) = p(x_i|C_k) \implies p(x_1, \dots, x_n|C_k) = \prod_{i=1}^n p(x_i|C_k)$$

- **Underlying Math**

Fig: <https://brilliant.org/wiki/naive-bayes-classifier/>



Hands on: Naive Bayes classifier

- Finally:

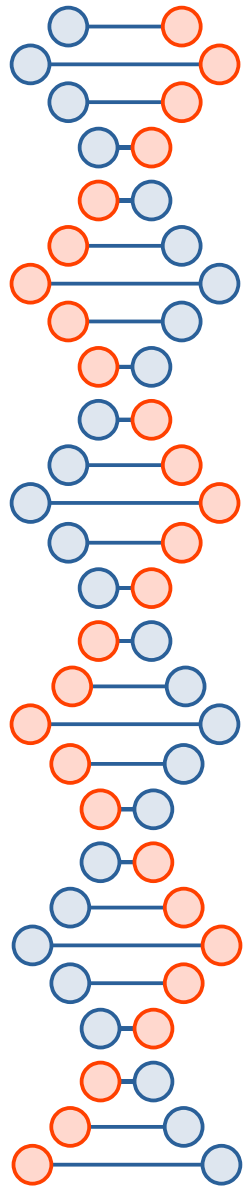
$$\begin{aligned} p(C_k | x_1, \dots, x_n) &\propto p(C_k, x_1, \dots, x_n) \\ &\propto p(C_k) p(x_1, \dots, x_n | C_k) \\ &\propto p(C_k) p(x_1 | C_k) p(x_2 | C_k) \dots p(x_n | C_k) \\ &\propto p(C_k) \prod_{i=1}^n p(x_i | C_k). \end{aligned}$$

- **Underlying Math**

- Classification:

$$\hat{C} = \operatorname{argmax}_{k \in \{1, \dots, K\}} p(C_k) \prod_{i=1}^n p(x_i | C_k)$$

where \hat{C} is the estimated class for \vec{x} given its features x_1, \dots, x_n .



Hands on: Naive Bayes classifier

- Input:

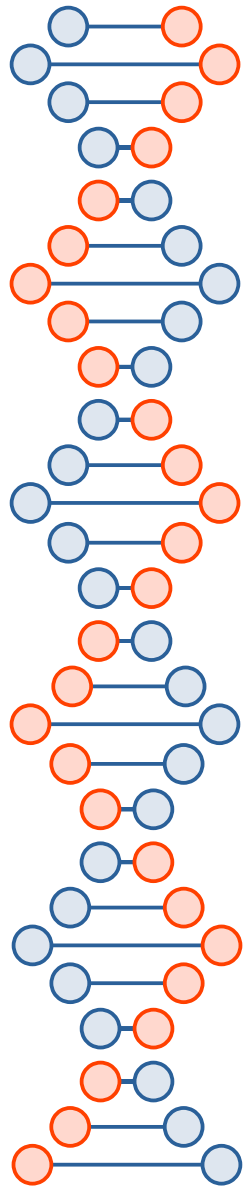
- a. Set of about 1000 words encoded in TTF fonts(Preeti, Kantipur) for Nepali language like खुवाउने, रमाए and so on.

- Output:

- a. For words : खुवाउने, रमाए >> the language is Nepali.

- b. For words : enjoy, eat >> the language is English.

- **Project Problem**



Hands on: Naive Bayes classifier

- Summary Outcome:

Total Models : 2

Nepali Grams Size: Probability of Language = -0.09570586672722367, Total Gram Entries : 921478

English Grams Size: Probability of Language = -2.393946991039648, Total Gram Entries : 140760

Classifier Results:

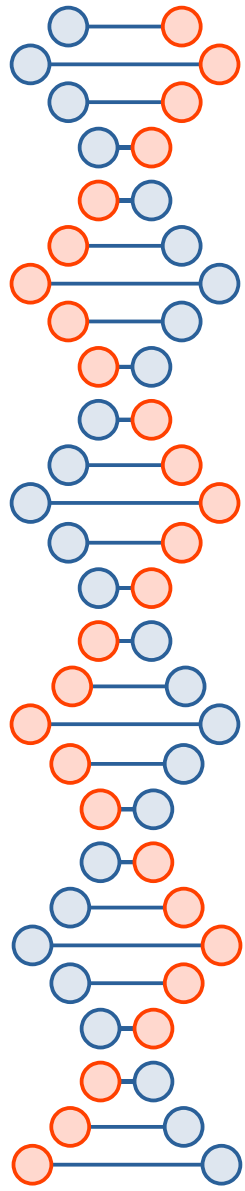
Word = {text='software'} >> Language{code='en', name='English'}

Word = {text=';^6jo]/'} >> Language{code='np', name='Nepali'}

Word = {text='nepali'} >> Language{code='en', name='English'}

Word = {text='g]kfnl'} >> Language{code='np', name='Nepali'}

Word = {text='nationality'} >> Language{code='en', name='English'}



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Questions ?